BeagleBadger Water Leak Detection System

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1 Introduction

Water use and plumbing system management are topics of increasing importance within the context of the smart home and the Internet of Things. Broad-based concerns of water conservation, health risk mitigation, and home property protection all entail a more flexible, sensitive approach to detecting water use anomalies, i.e. leaks and bursts. The BeagleBadger project, a portmanteau of the BeagleBone embedded computer board and Badger Meter water meter brands, combines the greater computing power now available to hobbyists with existing water meter 'hacking' techniques to create a system that can analyze and learn patterns from water use time series, allowing for the continuous monitoring of home plumbing systems. Synthesizing well-tested innovations in these various fields thus enhances the scope and capabilities of water use monitoring.

BeagleBadger is designed to bypass the expense or functionality limitations of previous approaches to water leak detection. First, BeagleBadger uses carefully set water use thresholds to detect small leaks. Expanding on previous work analyzing water use patterns of medium-sized residential populations in the US and Australia, we aim to detect a those situations when water flow is often at very low levels but fails to completely stop. Second, to detect larger water 'bursts,' such as those from a ruptured pipe or broken appliance, BeagleBadger uses a One Class Support Vector Machine (SVM) unsupervised learning algorithm, an approach to machine learning that has grown to be widely accepted in the past two decades. Because residential plumbing functions as a closed pressure system, the closing and opening of fixtures in a home creates pressure waves in the plumbing network. Recent research at the University of Wisconsin has demonstrated that the waves created by each fixture have relatively *unique* and *stable* features, providing a signature of sorts. Although previous approaches to this 'signature identification' problem have focused on careful calibrating to learn signatures for specific fixtures one-by-one,[1] we believe that and appropriate training time period would allow the SVM algorithm learn signatures in a user friendly and efficient manner.[2] BeagleBadger

[1] For example, the Hydrosense system, explored below, requires a period of calibration given that it aims to estimate the water flow from each fixture and not just identify the signature.

[2] Our approach leverages the insights from Huali Chen et al., "Application of Support Vector Machine Learning to Leak Detection and Location in Pipelines" (2004);Yongjin Wang et al., "Analysis of Human Electrocardiogram for Biometric Recognition", *EURASIP J. Adv. Signal Process* 2008 (Jan. 2008); Edison Thomaz

would then be able to continuously monitor usage for unusual signatures, which it would then flag as ' bursts.'

Below is an overview of our motivations and goals, followed by a short review of previous water leak detection efforts. We then present our approach and detail specific system elements and modules. Lastly, because of our team ' s difficulties in adapting existing Arduino sensor circuit designs to the BeagleBone, we were unable to carry out the testing and training experiments in the original project proposal. As such, we use synthetic data based on previous state of the art to evaluate the performance of the BeagleBadger in measuring water flow, learning fixture signatures, and detecting small leaks and large bursts. Given that each of these specifics modules is based on existing and replicable work, and given that plumbing flow is relatively well understood, we believe that using synthetic water flow data is a reasonable way to demonstrate the utility and feasibility of combining water meter monitoring and machine learning to create a leak detection system.

2 Background, Motivations and Related Work

Our work is motivated by attempts to mitigate environmental degradation, household health risks, and property damage. Water conservation is an increasingly important concern today, with states such as California and countries such as Australia experiencing increasing acute water shortages.[3] To date most approaches have focused on modulating water use or encouraging "greener" consumption patterns,[4] not taking into account that leakage accounts for up to 7.5-12 percent of residential water consumption in some areas.(Britton, Stewart, and O'Halloran, "Remote Diagnosis of Leakage in Residential Households")

Likewise, current approaches to home plumbing management ignore the roles played by mold and moisture in damaging long-term health, causing problems such as chronic respiratory illnesses.

Moreover, water leakage can lead to significant property damages. Most types of water damage, including mold, are not covered by home insurers, and as such poor management of home plumbing can lead to high financial losses and even the loss of coverage.

We believe that these decades-long problems can be resolved by combining new technological advancements in embedded computing and digital platforms, i.e. the Internet of Things, to produce smarter home plumbing management systems. Leak detection is a well established practice in various disciplines, most notably oil and

et al., "Recognizing Water-based Activities in the Home Through Infrastructure-mediated Sensing" UbiComp '12 (2012): 85–94

[3] See P.H. Gleick, *Waste Not, Want Not: The Potential for Urban Water Conservation in California* (Pacific Institute for Studies in Development, Environment, and Security, 2003)

[4] E.g. the California Water Foundation 1-year study showing that when participants received information comparing their water consumption to neighborhood averages, usage decreased by 5 percent on average. For study results see http://www.prnewswire.com/news-releases/new-technology-reduces-home-water-use-by-5-240121311.html; for more information on IoT approaches to water consumption management see http://siliconangle.com/blog/2014/03/03/the-internet-of-things-and-water-conservation-coping-with-nature-with-big-data-and-sensors/

gas transport[5] as well as large-scale irrigation.[6] Extending tried-and-true practices is thus suitable for providing numerous benefits within the context of the home.

2.1 Current State of the Art

Current approaches to leak detection can be classified as follows:

- ***Utility data analysis:*** Current approaches pioneered in Queensland, Australia, rely on analyzing water usage statistics for a residential population.[7] By comparing water use during low consumption periods, utility companies can identify usage outliers as homes with potential leaks.[8] The disadvantages of this approach are the need for population-level data and the inability to identify leaks in real-time, although combined with network analysis techniques they have proven useful for finding leaks in utility-level piping distribution.[9]

- ***Distributed sensing:*** With multiple microphones or accelerometers throughout the plumbing system, it is possible to identify water flow throughout the system. [10] In addition, knowledge of piping diameter in combination with calibration exercises can provide accurate estimates of water flow to any fixture. Anomalous signals produced by leaks can be easily detect and their location identified with relative ease. The practical obstacle to these systems is the installation and replacement of sensors, given that most plumbing systems are behind walls or beneath floors.

- ***Fixture control:*** Systems like the Italian-made Elettronico provide integrated water fixtures, LCD interfaces, and system-wide connectivity in one unified package. Although in development since 2008, the most developed product in the Eletrronico line is a motion-activated faucet module with touch-screen. With shower and bathroom fixtures under development, it is expected that in addition to remote fixture control, direct monitoring of most water fixtures al-

[5] Santosh Kumar Mandal, Felix T. S. Chan, and M. K. Tiwari, "Leak Detection of Pipeline: An Integrated Approach of Rough Set Theory and Artificial Bee Colony Trained SVM", *Expert Syst. Appl.* 39.3 (Feb. 2012): 3071–3080

[6] See the PowWow big data system for farmers at https://www.powwowenergy.com

[7] C.f. Britton, Stewart, and O'Halloran, "Remote Diagnosis of Leakage in Residential Households"; Tracy Britton, Rodney Anthony Stewart, and Kelvin O'Halloran, "Smart metering: providing the foundation for post meter leakage management", *International Water Association (IWA) Efficient* (2009);Tracy C. Britton, Rodney A. Stewart, and Kelvin R. O'Halloran, "Smart metering: enabler for rapid and effective post meter leakage identification and water loss management", *Journal of Cleaner Production* 54 (2013): 166–176

[8] The predefined period of low consumption is usually late night hours from 1 to 4 AM. It was found that 2 percent of meters accounted for 24 percent of recorded consumption. Additionally, users whose consumption does not reach zero in any given 48 hour period or whose use patterns are constant or monotonically increasing, are flagged for potential leaks.

[9] Adam Nowicki and Michal Grochowski, "Kernel PCA in Application to Leakage Detection in Drinking Water Distribution System." Lecture Notes in Computer Science 6922 (2011): 497–506

[10] C.f. Masanobu Shinozuka et al., "Non-invasive Acceleration-based Methodology for Damage Detection and Assessment of Water Distribution System", *Smart Structures and Systems* 6.5 (July-August 2010), <http://dx.doi.org/10.12989/sss.2010.6.5_6.545>: 545–559; Younghun Kim et al., "NAWMS: Nonintrusive Autonomous Water Monitoring System" SenSys '08 (2008): 309–322

lows for easier detection of leaks - if the the water meter detects water flow when all fixtures detect none then the plumbing system is at fault. The disadvatnage to such a system is cost and compatibility. Cost estimates for the Elettronico faucet run upwards of 200 USD, thus with the average home having 10-20 fixtures, installation costs can be prohibitive.[11]

- ***Wetness detection:*** Wetness sensors are relatively simple contraption whereby an alert is triggered if current flows between two exposed electrodes.[12] This is currently the approach pioneered by Xfinity, for the cost of 50 USD. Unfortunately such an approach is highly localized, and enough water must first be present to allow current between the two electrodes.[13]

- ***Single-point pressure sensing:*** HydroSense is a device currently being developed at the University of Washington, it utilizes a single high-pressure sensor to detect fixture openings and closings throughout the plumbing system, which it senses through the pressure transients that these vents generate.Pressure transients occur when the kinetic energy differential from stopping moving fluid or releasing static fluid is transformed into pressure. They are visible as oscillating pressure disturbances which then converge to a new pressure level. Transients are well-studied, particularly in the field of oil and gas transport. With calibration work done on each fixture it is then possible to detect and estimate water flow throughout the home.[14] Besides the cost of the high-pressure sensor, which can run upwards of 200 USD, using pressure for water flow sensing does not allow detection of small constant leaks, which do not produce pressure transients. [15]

Our goals are to overcome the shortcomings of each of the existing methods, allowing for the single-point, real-time detection of any size leaks.

3 Approach

Our device, tentatively named the BeagleBadger, furthers the smart home and IoT vision, giving users a view into, and control over, vital home systems. To do so, we make use previous work about 1) obtaining water meter data (Cheung Gregory), 2) small leak behavior(Britton, Stewart, and O'Halloran, "Remote Diagnosis of Leakage in Residential Households"), and 3)home plumbing pressure transients(Froehlich et al.) which are then exploited through 4) machine learning methods(Chen et al. Wang et al. Thomaz et al.). In this respect our project is a synthesis of previous work based on the insight that proper time series analysis can allow a an algorithm to continuously monitor the usage in a home.

[11] For more on the Elettronico faucet, produced by FIMA - Carlo Frattini see http://www.fimacf.com/it/index.aspx

[12] For a more technical description of this type of sensor see "Water Leak Liquid Sensor Specifications" (), <http://www.wateralert.com/specifications.php>

[13] For more information see www.xfinity.com

[14] https://homes.cs.washington.edu/~jfogarty/publications/ubicomp2009.pdf

[15] Jon Froehlich et al., "HydroSense: infrastructure-mediated single-point sensing of whole-home water activity." ACM International Conference Proceeding Series (2009): 235–244

4 System Description

The leading build of residential water meters operate using a fixed-displacement system. As the water flows through the meter, it causes a disk to nutate inside the encasing. Each nutation corresponds to a fixed volume of water, estimated to be 1/50th of a gallon.(Cheung) The disk rotates a magnet which then moves the dial on top of the meter, recording water flow.

Our system is comprised of a hall effect sensor module that is designed to detect water flow, which is the approach used in (Kim et al.) and which we build using information from (Cheung) and (Gregory). The signal is then processed to produce a time series of water flow. It is then used in small leak detection and large burst detection algorithms. The large burst algorithm would ideally be trained on a particular home system for a period of a week, and a user interface would allow direct intervention in the system via remote-operated flow-interruption valves.

4.1 Sensor Module

We went through several iterations of sensor setups in order to arrive at one that gave us the clearest, most accurate signal. We started by connecting a hall effect sensor to an analog IO pin on the BeagleBone Black, which our python script then queried at 20Hz. This frequency is adequate since a showerhead can use up to 7 gallons per minute, and at 50 rotations per gallon causes 6 nutations within the water meter magnet, and the Nyquist rule suggests that we need at least 12Hz (= 6 rotations per second * 2). Data is then uploaded to a CouchDB database in the cloud, is also stored locally in a csv file for further processing. This module, based on information found online from hobbyist Ed Cheung's 2003 project,[16] can be seen in Figure 1.

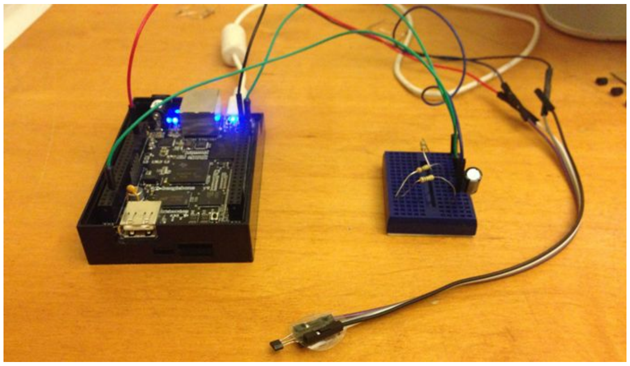

Figure 1: BeagleBone and Hall effect sensor.

Unfortunately, this setup did not quite work as well as desired. The Hall effect (HE) sensor can output up to 5 Volts, while the BeagleBone analog IO pins accept a maximum of only 1.8 Volts. This would cause signal clipping as the magnet approached the sensor, giving a poor signal reading. Adding a voltage divider to proportionally lower the output voltage from 5 V to 1.8 V produced an output voltage independent of sensor readings or circuit adjustment. We hypothesize this may be due to insufficient resistance in the voltage divider as compared to the sensor load.

A second module we built was composed of a Spark IO unit and some basic circuitry around the HE sensor. The unit would then upload data to the Spark database online, which would then be queried for processing. Unfortunately we discovered that the Spark IO unit can only upload a maximum of 20 data points per minute, making the signal unusable.

A third module involved altering one of the existing, pre-built Hall effect sensor modules available for Arduino robots and cars. Needless to

[16] Cheung

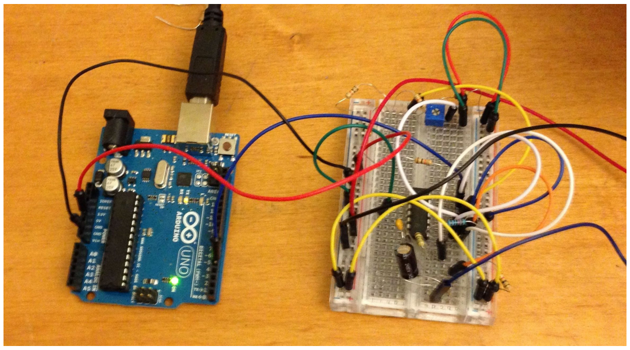

Figure 2: Arduino with Instructables setup.

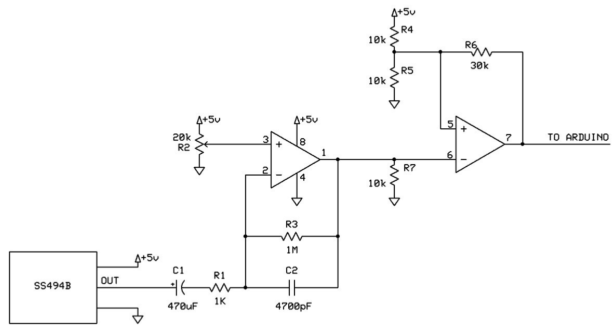

Figure 3: Circuit diagram for Arduino.

say, because those modules are built to detect stronger magnetic signals, the sensitivity was too low to detect the water meter rotations.

Lastly, we used an Arduino, allowing us to use a Hall effect sensor module built specifically for reading water meters which we found online at Instructables,[17] which can be seen in Figure 3. This can then be connected to the BeagleBone Black for processing. Our original goal was to adap the Instructables design to the BeagleBone, but this consumed too much of our project's time. We believe that with a longer deadline this setup could be adapted for the BeagleBone voltage requirements, eliminating the need for the Arduino.

The Arduino originally in the 5 Volt signal as a digital signal (with the magnet being either close enough or not close enough to the sensor), and output that signal through a voltage divider to an analog IO pin on the Beaglebone, which then recognizes the signal as either 0.9 or 0.0. We decided to add a 5-1.8 V voltage divider as well as a 470F capacitor connected directly to the BeagleBone analog IO pin. This produced the signal behavior we wanted: the reading was ratiometric, with the tenths and hundreths digits giving the correct flux without noise. The below sections are described assuming this kind of behavior, which is consistent with the previous literature. This final module can be seen in Figure 2

Unfortunately the given the order lead times for ordering components and for replacing a broken BeagleBone, we have not had enough time to deploy our module to gather enough testing and training data. Thus, we have used synthetic data modeled on the signal behavior described in past literature, primarily in (Froehlich et al.) for large bursts and (Britton, Stewart, and O'Halloran, "Smart metering: enabler for rapid and effective post meter leakage identification and water loss management") for smaller leaks.

4.2 Signal Procesing

We built a circuit based on the diagram in Figure 3 to amplify and filter the periodic signal from the Hall effect sensor. In addition, a potentiometer in the circuit allowed us to adjust the distance at which the Hall effect sensor would detect a magnetic signal, in effect changing the sensitivity of the sensor. However, we discov-

[17] Gregory

ered this sometimes caused unexplained "latching" behavior, where the signal would jump and stay fixed for a certain amount of time.

We added a $470\mu F$ capacitor in series with the Hall effect sensor output to remove the quiescent voltage from the signal, filtering the background voltage from the sensor output, leaving us only with the magnitude of the periodic signal over time.

To translate the magnetic flux data into a water flow series, we first use Gaussian smoothing on the signal, then identify the maxima, which correspond to meter disk nutation, and store these as a list of timestamps $[t_0, ..., tn]$. Knowing from (Cheung) that the fixed volume k displaced by each nutation is 1/50th of a gallon, we use $k/\Delta t_1$ where $\Delta t_n = t_{n+1} - t_n$, to deduce the water flow at time t_1. We thus produce a list of the form $[[t_0, k/\Delta t_0], ..., [t_{n-1}, k/\Delta t_{n-1}]]$, composed of pair of time and waterflow values $[T_n, Q_n]$.

4.3 Small Leak Detection

Using the time and waterflow list for the last 12 hours, we locate all local minima. We define a threshold for "zero" waterflow, as $k/\Delta t$ cannot ever be zero, and ignore all minima that occure before the last "zero" waterflow event - such an event is evidence that the system does not have a small leak as no water is flowing through the meter. For the remaining local minimia, if we find 3 values which are similar enough and lie within range ϵ of the zero threshold, then we create a small leak alert. A repeating small waterflow value indicates that although all fixtures are closed, a small leak still registers flow through the plumbing system. This aproach mimics that found in (Britton, Stewart, and O'Halloran, "Remote Diagnosis of Leakage in Residential Households") and (Britton, Stewart, and O'Halloran, "Smart metering: providing the foundation for post meter leakage management"), which also describe small leak behavior as constant over the medium term (a few days).

4.4 Large Leak Detection and training

Successful reading and learning of pressure transient signatures from valve closing and openings requires careful attention to feature extraction.[18] This process involves identifying the proper transient signal, identifying their features, and using the right algorithm to learn those features.

First, waterflow series must be used to identify pressure transients. As noted in (Froehlich et al.), Poiseuille's law gives the pressure drop between two ends of a pipe,

$$Q = \frac{\Delta P \pi r^4}{8\mu L} \tag{1}$$

where P is pressure, r is pipe radius, L is pipe length, and μ is fluid viscosity. Given that with the exception of P all other values are relatiely constant, we can simplify the equation using the definition of resistance to flow R_f to get,

$$Q = frac\Delta P R_r, s.t. R_f = \frac{8\mu L}{\pi r^4} \tag{2}$$

With this equation in mind, ΔQ then gives us the change in the change in pressure between the two ends. Thus given that the pressure at the first end P_a is constant over the short- and medium- terms (it is regulated by utilities),

$$Q = P_b R_f - P_a R_f \Rightarrow \Delta Q = -R_f \Delta P_b \tag{3}$$

[18] Gustavo E. A. P. A. Batista, Xiaoyue Wang, and Eamonn J. Keogh, "A Complexity-Invariant Distance Measure for Time Series." (2011): 699–710

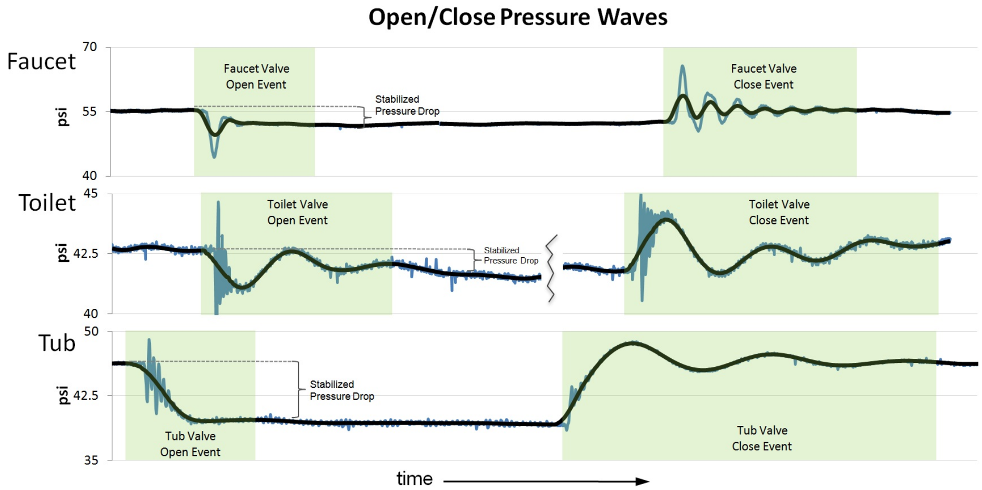

Figure 4: Pressure transients for different fixtures, with shaded areas representing opening and closing events. From HydroSense by Froehlich et al.

The change in water flow is thus proportional to the change in water pressure from fixture closings and openings.

It is then possible to create data series analogous to those in Figure 4 by using the $[T_{n-1}, Q_{n-1}]$ waterflow data list and to create a list of the form $[[\Delta t_0, \Delta q_0], ..., [\Delta t_{n-2}, \Delta q_{n-2}]]$. Since R_f is constant we ignore it for our purposes.

To identify opening and closing events it is necessary to locate big changes in pressure (Froehlich et al.). Given we cannot directly measure the home's static pressure, we mark the beginning of these events when dQ/dt exceeds 0.5 gl/s, and mark the end of the event when d^2Q/dt^2 fluctuates by less than 5 percent per second.[19]

[19] Our approach here differs from (Froehlich et al.), who mark events when dP/dt exceeds 5 percent of static pressure, ending when the local maxima of dP/dt is less than 5 percent of the event's first local maximum.

Building off work done by (()chenye2004), (Wang et al.), and (Thomaz et al.), once the signal has been segmented we use a One Class Support Vector Machine (SVM) to learn the signatures. We do this by extracting three consecutive local extrema in the ΔP_b series. These three extrema capture three features of the oscillation,

1. Frequency: given by the average time between extrema

2. Maximum amplitude: given by the range between the highest and lowest extrema

3. Convergence pressure: given by the middle value between the highest and lowest extrema

From these three features we can create a three-dimensional vector to train the One Class SVM, allowing the algorithm to learn the signature of various fixtures and thus create an alarm when a new rapid water flow event arises.

Although various other features could have been extracted, especially given that (Froehlich et al.) uses four distance measures very different from ours, our particular learning algorithm successfully classifies numerous synthetically created signals based on those found in the literature.[20] We further believe that to limit the processing demands on the BeagleBone, feature extraction and processing should not be made overly complex.

4.5 User Interface and System Intervention

Our original project initially envisioned a way for users to interact with their system. At the moment, waterflow data could be uploaded to a web repository, potentially allowing users to see their water usage. However, more time would be needed to add an interactive UI. Future expansion might include remote control of shut-off valves as well.

5 Performance Evaluation

Given the obstacles that our team faced in building a working meter-reading sensor, performance must be done on the basis of synthetic data.

Our algorithms perform as expected. BeagleBadger can identify recurring non-zero waterflow values as well as pressure transients different from those found in its training set.

Still, several key questions remain which can only be answered experimentally with more time for testing. First, the proper threshold for small leak detection has to be determined by testing in various pipe setups, for it is possible that a small leak will form which might fall within the definition of "zero" or which might be above the maximum defined for "low-flow." More importantly, different types of burst leaks must be simulated, potentially at significant expense, to simulate signatures coming from different type materials and aperture sizes. It might very well be the case that we will need a feature extraction process more in line with that found in (Froehlich et al.), which has an aggregate accuracy of about 98 percent but at a greater processing power cost. Potential alternatives include sliding window one-dimensional smoothing(Wang et al.), matched filtering, matched derivative filtering, real Cepstrum,[21] or mean-squared error.

6 Conclusion

BeagleBadger brings together various insights and approaches, all of which have been tested and validated in previous work. Our contribution is an attempt to piece these disparate ideas together and modify them to suit the constraints of an embedded computing system such as the BeagleBone, vastly broadening the field of application and allowing constant monitoring with near-real-time leak detection.

Although we remain confident that our approach is the correct one, more time is needed to experimentally determine the specifics of our small leak detection thresholds and of our large leak feature extraction choices.

[20] Broadly speaking, they tend to resemble exponentially decreasing sinusoids.

[21] The inverse Fourier transform of the natural logarithm of the magnitude of a signal's Fourier transform

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